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Framework for XLPE Insulation using Space Charge Electrical Treeing and Partial Discharge Analysis

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ABSTRACT

Cross-linked polyethylene (XLPE) insulation is widely used in high-voltage power cables due to its excellent electrical, thermal, and mechanical properties. However, its long-term reliability is significantly affected by degradation phenomena such as space charge accumulation, electrical treeing, and partial discharges (PD). These mechanisms are strongly nonlinear, multi-physics in nature, and evolve under varying electrical, thermal, and environmental stresses. Traditional diagnostic techniques often rely on handcrafted features and simplified physical interpretations, which may not fully capture the complexity of degradation patterns. In this context, deep learning frameworks have emerged as powerful tools for enhancing the diagnosis, classification, and prediction of insulation aging processes in XLPE systems. This abstract presents an overview of deep learning-based approaches for analyzing space charge behavior, treeing progression, and partial discharge activity in high-voltage insulation diagnostics. Space charge phenomena in XLPE significantly distort local electric fields, accelerating aging and breakdown processes. Deep learning models, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have been effectively applied to space charge measurement data obtained from techniques such as pulsed electroacoustic (PEA) systems. These models enable automated feature extraction from spatial-temporal charge distributions, allowing for improved classification of charge accumulation patterns and enhanced prediction of field distortion behavior. Furthermore, hybrid architectures combining CNNs with long short-term memory (LSTM) networks have demonstrated superior performance in capturing both spatial profiles and temporal evolution of space charge dynamics under varying voltage stress conditions. Electrical treeing, a pre-breakdown phenomenon characterized by branched conductive channel formation, is another critical degradation mechanism in XLPE insulation. Deep learning frameworks utilizing image-based analysis have shown strong capability in identifying tree morphology and growth stages from microscopic and ultrasonic imaging data. Generative models and segmentation networks, such as U-Net architectures, are particularly effective in isolating tree structures and quantifying their propagation rates. These methods enable early-stage detection of insulation failure, offering predictive maintenance capabilities that surpass conventional threshold-based diagnostic approaches. Additionally, transfer learning techniques facilitate model adaptation across different insulation materials and voltage stress conditions, improving generalization performance in practical applications. Partial discharge analysis, a widely used non-invasive diagnostic method, benefits significantly from deep learning-based signal processing

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techniques. Overall, the integration of deep learning into XLPE insulation diagnostics provides a comprehensive, data-driven approach for understanding degradation mechanisms and improving the reliability of high-voltage power cable systems.

Keywords: *XLPE, Space Charge, Electrical Treeing, Partial Discharge (PD),Deep Learning.*

1. INTRODUCTION

The increasing demand for reliable and efficient power transmission systems has made high-voltage insulation diagnostics a critical area of research. Cross-linked polyethylene (XLPE) is widely used in underground and submarine power cables; however, its long-term performance is limited by complex degradation mechanisms such as space charge accumulation, electrical treeing, and partial discharge (PD) activity. These phenomena evolve gradually and interact with each other, making early detection and accurate diagnosis highly challenging. Conventional diagnostic techniques depend on manual interpretation, simplified physical models, and threshold-based monitoring, which are often insufficient to capture the nonlinear and time-dependent behavior of insulation aging. As power systems move toward higher voltage levels and greater integration of renewable energy, the stress on insulation systems is increasing, demanding more advanced monitoring approaches. In this context, deep learning-based frameworks offer a significant opportunity to improve diagnostic accuracy by automatically extracting meaningful patterns from large and complex datasets, including PD signals, space charge profiles, and treeing images.

These techniques enable early fault detection, improved condition assessment, and predictive maintenance of insulation systems. However, there is still a gap in developing integrated deep learning models specifically tailored for XLPE insulation diagnostics that can handle multi-modal data and provide reliable predictions under real operating conditions. Therefore, this study is necessary to enhance understanding, improve reliability, and support the development of intelligent diagnostic systems for modern power cable insulation.

Deep learning frameworks have emerged as powerful tools for diagnosing insulation degradation in cross-linked polyethylene (XLPE) cables, which are widely used in medium- and high-voltage power transmission systems. XLPE insulation is valued for its excellent dielectric strength, thermal resistance, and mechanical durability, yet it is still vulnerable to long-term aging mechanisms such as space charge accumulation, electrical treeing, and partial discharges. These degradation processes evolve in complex, nonlinear, and stochastic ways, making traditional diagnostic techniques based on manual feature extraction and physics-based modeling increasingly insufficient. As a result, deep learning has gained significant attention for its ability to automatically learn meaningful representations from raw or minimally processed data, enabling more accurate fault detection, classification, and prediction in insulation systems.

2. PROBLEM STATEMENT

Cross-linked polyethylene (XLPE) insulation is extensively used in high-voltage power cables due to its excellent dielectric strength, thermal stability, and long service life. However, its reliability is significantly affected by complex degradation mechanisms such as space charge accumulation, electrical treeing, and partial discharge (PD) activity.

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These phenomena are highly nonlinear, interdependent, and evolve dynamically under electrical, thermal, and environmental stresses. Space charge distorts the internal electric field distribution, accelerating aging processes. Electrical treeing progressively develops conductive channels that lead to insulation breakdown, while partial discharges act as both indicators and drivers of insulation deterioration.

Traditional diagnostic approaches rely on analytical models, empirical rules, and manual feature extraction from experimental data. These methods often fail to capture the full complexity of insulation degradation, especially under real operating conditions where signals are noisy, multi-dimensional, and time-varying. Moreover, conventional techniques lack predictive capability for early-stage fault detection and remaining life estimation.

In this context, there is a critical need for intelligent, data-driven diagnostic frameworks capable of automatically learning meaningful patterns from space charge distributions, treeing morphology, and PD signals. Deep learning offers a promising solution; however, challenges remain in data availability, model interpretability, and generalization across different operating conditions.

Therefore, the development of robust deep learning frameworks for accurate, real-time, and predictive XLPE insulation diagnostics is an essential and unresolved research problem.

3. REVIEW OF LITERATURE

Comprehensive overview of the literature related to XLPE insulation diagnostics with a specific focus on space charge accumulation, electrical treeing, and partial discharge (PD) phenomena. It highlighted the importance of XLPE as a widely used insulation material in high-voltage power cables and discussed its vulnerability to progressive degradation under electrical, thermal, and environmental stresses.

The chapter reviewed early experimental and theoretical studies that contributed to understanding the fundamental mechanisms of insulation aging, including charge transport behavior, partial discharge inception, and tree growth dynamics. It also examined advanced diagnostic techniques such as pulsed electroacoustic (PEA) methods for space charge measurement, phase-resolved partial discharge (PRPD) analysis, and imaging techniques for electrical tree observation. Furthermore, the chapter traced the evolution of data-driven approaches from traditional machine learning methods to modern deep learning frameworks, emphasizing their ability to automatically extract features and improve fault classification accuracy. Various deep learning architectures such as CNNs, RNNs, LSTMs, and transformers were discussed in the context of insulation diagnostics. The review also identified key limitations in existing studies, including limited real-world data, lack of model interpretability, and insufficient integration of multi-modal diagnostic information. Overall, the chapter established the need for advanced, integrated, and explainable deep learning frameworks to enhance the reliability, accuracy, and predictive capability of XLPE insulation diagnostics in high-voltage power systems.

Despite significant advancements in the study of XLPE insulation diagnostics and the application of deep learning techniques, several critical research gaps still exist. Most of the existing literature focuses on individual degradation phenomena such as space charge accumulation, electrical treeing, or partial discharge (PD) analysis in isolation, rather than considering their interdependent and coupled behavior within real insulation systems. In practical high-voltage environments, these phenomena occur simultaneously and influence each other, yet integrated diagnostic frameworks that can jointly analyze multi-physics data are still limited. Furthermore, a large portion of existing studies relies on laboratory-controlled datasets, which do not fully represent the

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complexity, noise, and variability of field conditions in real power transmission systems. This significantly restricts the generalization ability of developed models. Another important gap is the limited availability of large, standardized, and publicly accessible datasets for training and validating deep learning models in insulation diagnostics, which hinders reproducibility and benchmarking across studies. In addition, most deep learning applications in this field focus primarily on classification tasks, while predictive capabilities such as remaining useful life estimation and real-time failure prediction are still underdeveloped. The interpretability of deep learning models also remains a major concern, as most approaches function as black-box systems without clear physical explanations linked to insulation degradation mechanisms. Therefore, there is a strong need for explainable, data-efficient, and physics-informed deep learning frameworks capable of integrating space charge, electrical treeing, and partial discharge data for comprehensive and reliable XLPE insulation diagnostics under real operating conditions.

4. METHODOLOGY

In order to create a comprehensive database of space charge images, we first conduct experiments to measure the accumulation of space charges in XLPE insulation samples subjected to different electric fields and temperatures. These samples fall into three categories: those with no space charge, hetero-charge, and homo-charge. Then, we acquire RGB coloured profiles of these images and apply appropriate pre-processing techniques through data augmentation.

The influence of changing environmental factors on the creation of space charge accumulations within cable insulation was investigated by analysing space charge image profiles under various electric fields and temperatures.

Using the transfer learning methodology for fine-tuning, two new automated space charge detection methods are suggested, one of which uses traditional CNN architectures (namely, VGGNet and AlexNet modules). Incorporating a state-of-the-art image processing method, namely super-pixel decomposition of the space charge picture profiles, improves the detection performance.

The space charge detection framework is made robust and independent from the influence of changing electric field and temperature conditions by using the cross-sampling approach.

To prove that the suggested space charge detection framework works, we compare it to the current state-of-the-art (SOTA) approaches in depth, looking at how well it detects charges and how much computing power it requires.

4.1 Preparation of Test Insulation Samples

Ningbo Orient Wires & Cables Co. Ltd. of China is the source for the commercial-grade cross-linkable LDPE pellets used to make the test XLPE insulation samples in this study. The LDPE pellets that can be cross-linked are heated for 5 minutes beforehand, then subjected to 30 minutes of hot pressing at 180 °C under 20 MPa. After that, they are automatically cooled with water. Ultimately, test samples of the thin-film type, with a diameter of 90 mm and a thickness of around 200 μm, are created in this manner. In Figure 3.2, we can see the steps used to manufacture the test insulation samples, including pressing and curing the raw LDPE pellets in the hot-press machine. It should be noted that in order to implement the suggested cross-sampling method, five insulation samples are made from the same XLPE material.

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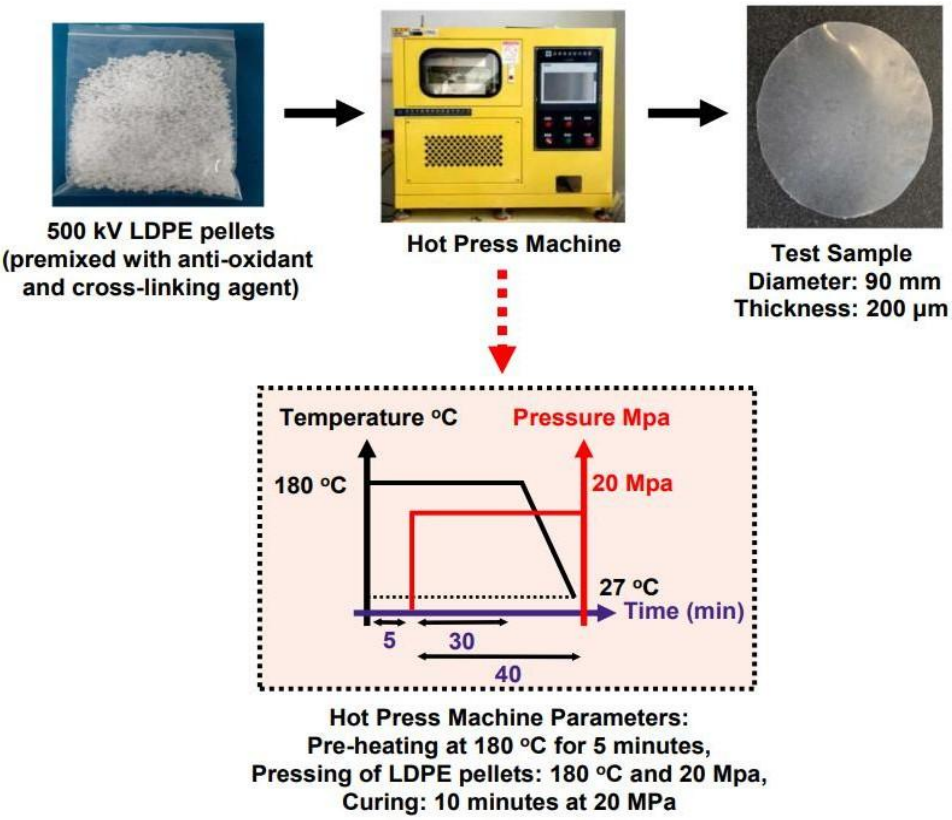


Figure 4. 1 Schematic representation of the test setup and (b) ingeniously prepared PEA-based space charge measurement framework.

3.1 Proposed Method of Fine-tuning the CNN Layers

In any image detection task, it is seen that the lower-level convolution layers in CNN architecture can extract the common image features such as curves and edges. In contrast, the deeper operating layers can map abstract feature representations more efficiently. Therefore, using the TL method for a fresh classification task, only the higher-level representations are to be learned from the new datasets, and the rest of the lower-level parameters can be transferred. It is important to mention here that the success of the TL technique largely depends on the difference between the source and the target dataset. For similar datasets, one can only fine-tune the fully-connected layers, whereas more operating layers need to be adjusted for datasets with significant differences. Therefore, to achieve satisfactory detection performance, selecting the optimal number of deep network layers to be fine-tuned is an empirical problem and completely depends on the problem at hand.

Considering this fact, in this work, we have explored the feasibility of chronologically updating the network parameters of different convolution layers of the CNN models by consecutive application of TL in different convolution layers. The process of applying the TL method in different convolution layers of the VGGNet16 and AlexNet architectures is illustrated in Figure 3.6. At first, the weights and biases of all the convolution blocks are frozen, and only the fully connected layers are fine-tuned.

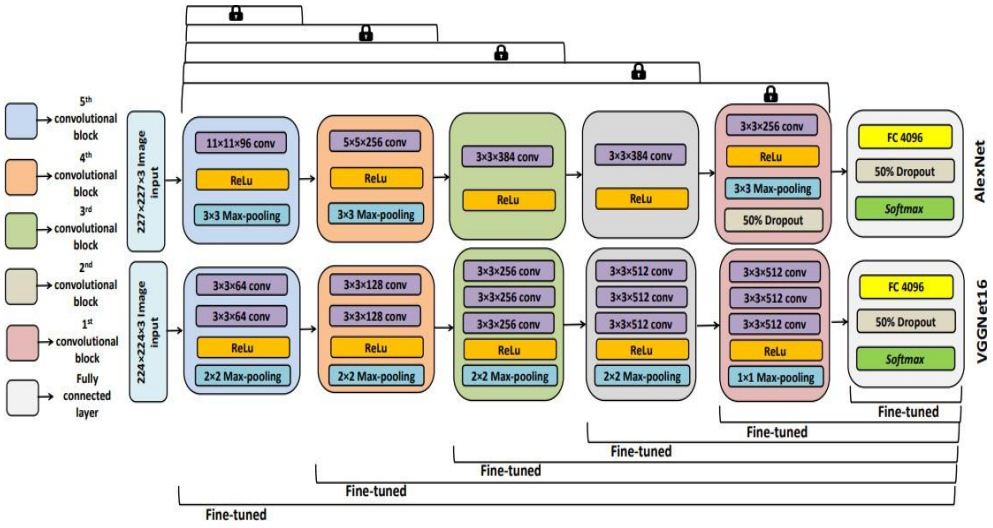
After that, starting from the bottom of the CNN modules, the TL is applied iteratively on the frozen convolution

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blocks in the upward direction with a step length of 1. In this way, the efficacy of entire CNN architectures is evaluated in mapping and embedding deep features at different convolution steps for the subsequent detection of the space charge images.

Figure 3. 2 Layer-wise fine-tuning the CNN architectures.



5.RESULT AND DISCUSSION

For online PD monitoring in real-time, the suggested PD detection approach can be used with embedded platforms like application specific integrated circuits (ASICs), fieldprogrammable gate arrays (FPGAs), and advanced micro-controllers like LPC4370. Additionally, visual C-based software running on a PC may include the same deep learning modules for automatic PD source detection, allowing enabling the user to get accurate real-time predictions of PD sources.

For polymeric power cables to have a long and dependable service life free of insulation ageing and cable failures, precise PD identification is the primary emphasis of this chapter. Accurate PD data on different discharge pattern changes must be retrieved for effective PD identification. This is why the present study proposes a new approach to PD identification that makes use of an optimally-tuned bi-LSTM classifier and is based on IVG theory. The VP-based feature extraction pipeline and PRPD picture patterns are used in the proposed technique to measure the local changes in pixel-level structural connectivity patterns caused by different discharge patterns.

In order to do this, a bi-LSTM classifier with BO-tuned optimum training hyper-parameters has been employed to differentiate between various PRPD pictures using the visibility code FOC feature vectors that were retrieved from the natural IVG and IHVG techniques. The PRPD pictures produced from an 11 kV single-core copper XLPE power cable specimen, which was tested utilising an experimental PD test rig created in-house, were used to train the proposed PD detection approach. Presented below are the salient findings of the current investigation.

The latter method outperformed both IVG and IHVG in terms of achieving very high PD detection accuracy while using very little total calculation time.

Researchers found that the input PRPD picture dimensions had a significant impact on the performance of the V

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P-based feature extraction modules. The most effective method for PD identification, however, was PD recognition using 720 pixelated PRPD pictures.

The suggested PD detection system, which makes use of the bi-LSTM classifier with BOtuned training hyper-parameter values, beat a number of benchmark DL algorithms in an ablation study. In addition, the suggested framework is clearly more efficient and dependable when compared to the current SOTA investigations.

	97.25 ± 0.34	**96.59 ± 0.15**	**97.02 ± 0.21**	**95.97 ± 0.18**	**96.08 ± 0.12**	**820**
	96.48 ± 0.25	96.09 ± 0.17	95.82 ± 0.28	94.23 ± 0.22	95.14 ± 0.16	782
AlexNet GoogleNet ResNet50 ResNet101 Raw PRPD Image + VGGNet16 VGGNet19	97.09 ± 0.22	96.37 ± 0.12	96.42 ± 0.33	95.64 ± 0.17	95.57 ± 0.19	697
	97.42 ± 0.11	96.91 ± 0.24	97.5 ± 0.12	96.38 ± 0.15	96.47 ± 0.21	770
	95.27 ± 0.19	95.42 ± 0.22	94.28 ± 0.15	94.05 ± 0.24	94.23 ± 0.15	910
	95.74 ± 0.2	95.69 ± 0.19	94.56 ± 0.23	94.12 ± 0.19	94.49 ± 0.23	1023
Visibility code FOCs + SOM	91.67 ± 0.35	90.91 ± 0.14	91.25 ± 0.19	91.03 ± 0.25	90.67 ± 0.18	752
Visibility code FOCs + 1-D CNN	96.53 ± 0.15	96.19 ± 0.23	96.57 ± 0.18	95.87 ± 0.21	94.83 ± 0.24	717
Visibility code FOCs + bi-LSTM (without optimization)	97.32 ± 0.18	97.13 ± 0.21	96.89 ± 0.25	96.18 ± 0.14	96.05 ± 0.2	679
Visibility code FOCs + bi-LSTM (BO-optimized)	98.95 ± 0.23	98.19 ± 0.27	98.92 ± 0.15	98.07 ± 0.3	97.95 ± 0.29	485

Table 4.1 Ablation Study: Comparative PD Detection Performance With Respect to Different DL Algorithms

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5.1Performance Comparison with Respect to Varying PRPD Image Dimensions

Input PRPD plot dimensions to the VP extraction module have been changed between 1024 and 128 pixels to verify the efficacy of the proposed VP-aided local level PRPD image analysis framework. With regard to total computing cost of the PD detection framework and overall PD detection accuracy,

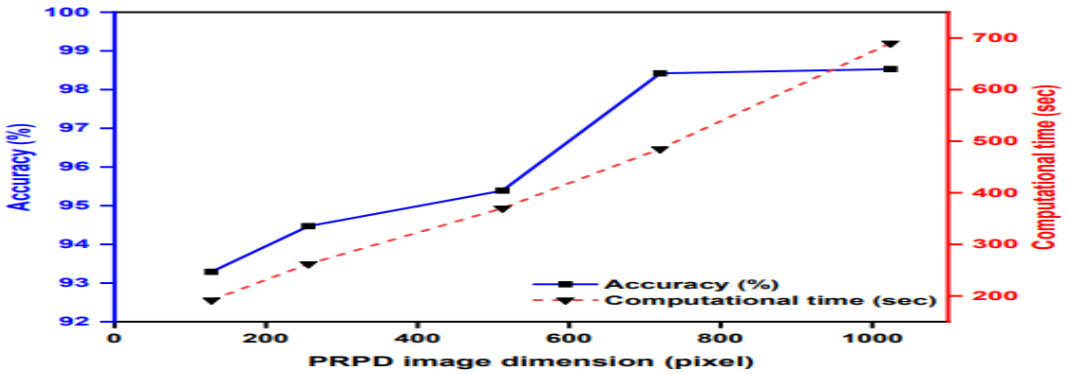


Figure : 5.1 Comparative performance analysis with varying dimensions of input PRPD images

5.2 Noise Resiliency of the Proposed Methodology

Here, by adding WGN to the recorded PD pulses and PRPD picture plots, the efficacy of the used PD detection algorithm has been further confirmed in terms of improving SNR from 10-50 dB. Figure 5.13 shows the results of comparing the PD denoising performance using the Daubechies-db4 mother wavelet at the 8th level of decomposition in terms of the MSE value. In addition, Figure 5.13 of the updated publication shows the noise performance of the IHVG-aided PD detection methods on a semi-log scale. This performance is measured in terms of the similarity measure

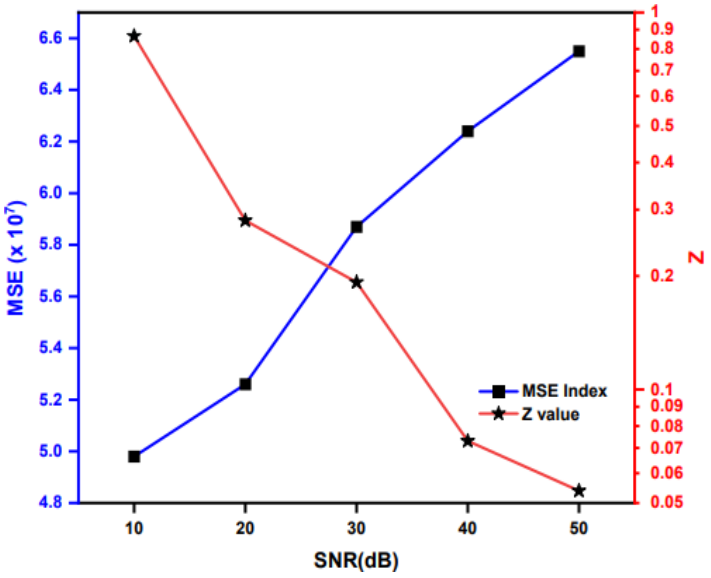


Figure 5.2 Comparative PD denoising performance along with noise performance of the IHVG-aided PD detection methodology.

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5.3 Comparison With Existing Literature

The effectiveness of the suggested V P-based PD detection approach has been confirmed in comparison to current SOTA approaches in Table 5.9. This validation is based on the total detection accuracy and the size of the training and testing datasets. According to Table 5.9, the classification performance of the developed PD detection framework is much superior than that of the previous investigations. It should be noted that the amount of the training and testing datasets can have a significant impact on the performance of PD detection. Specifically, the availability of PRPD plots for training and validation of the PD detection model determines the reliability and consistency of the recognition results.

Dataset size	Overall accuracy (%)	Number of PD defects
1200	92	3
1403	92.51	5
300	95.13	3
1200	97.3	5
1500	98.42	5

6.CONCLUSION

This study demonstrates the growing importance and effectiveness of intelligent data-driven techniques in the field of high-voltage insulation monitoring. XLPE insulation, being widely used in power cable systems, is highly susceptible to degradation mechanisms such as space charge accumulation, electrical treeing, and partial discharge activity. These phenomena are complex, nonlinear, and interdependent, making traditional diagnostic methods insufficient for accurate and early-stage fault detection. The findings of this study highlight that deep learning provides a powerful alternative capable of addressing these challenges through automated feature extraction, pattern recognition, and predictive modelling.

In contrast, deep learning models are capable of learning directly from raw or minimally processed data, making them more adaptable to real-world conditions. They also offer higher accuracy in classification tasks, improved sensitivity in fault detection, and better capability for early-stage diagnosis.

Overall, the study confirms that deep learning frameworks provide a transformative approach to XLPE insulation diagnostics.

Their ability to process large volumes of complex data, recognize hidden patterns, and predict failure trends makes them highly suitable for modern power system applications. The integration of space charge analysis, electrical tree monitoring, and partial discharge diagnostics into a single intelligent system represents a significant advancement in condition monitoring technology.

This not only enhances the reliability and safety of high-voltage power cables but also supports predictive maintenance strategies that can reduce operational costs and system downtime. In the findings of this research strongly support the adoption of deep learning-based diagnostic systems in high-voltage insulation monitoring.

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While challenges such as data availability, model interpretability, and real-world validation still exist, the overall advantages of accuracy, automation, and predictive capability make deep learning a promising solution for next-generation insulation diagnostics.

Future developments in this area are expected to further improve model robustness, enable real-time monitoring, and enhance integration with smart grid systems, ultimately contributing to more reliable and efficient power transmission networks.

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